## IN THE CLAIMS

Please amend the claims to read as shown below.

## Change Claims to:

- 1 78. (cancelled)
- 79. (new) A method of building predictive models from transaction data, comprising:
  - aggregating data from a plurality of transaction systems covering a series of time periods for one or more elements and one or more outputs;
  - transforming said element data in accordance with one or more pre-programmed functions;
  - establishing a plurality of input nodes, a plurality of hidden nodes and an output node for a neural network model for each output;
  - inputting the raw and transformed transaction data into each neural network model using a separate input node for untransformed transaction data and each preprogrammed transformation function by element for all time periods in the series;
  - training each neural network model using said inputs until an error function associated with an output value is minimized; and
  - using one or more weights from the trained neural network models to identify a set of raw and transformed transaction data by element and output that will be used as an input to one or more predictive models.
- 80. (new) The method of claim 79 where a plurality of input nodes is set equal to one plus the number of elements times one plus the number of pre-programmed functions used to transform transaction data.
- 81. (new) The method of claim 79 where a plurality of hidden nodes is set equal to one plus the number of input nodes.
- 82. (new) The method of claim 79, where an error function further comprises ERR (W)<sub>k</sub> =  $1/2 (R_k Y(W))^2$ .
- 83. (new) The method of claim 79 where a set of raw and transformed transaction data that will be used as an input to a predictive model further comprises a set of numbers.

84. (new) The method of claim 79 where one or more predictive models further comprises one or more neural network models.

85. (new) The method of claim 79 where training a neural network model further comprises using a genetic algorithm to complete the training.

86. (new) The method of claim 79 where training a neural network model further comprises using a back propagation algorithm to complete the training.

87. (new) The method of claim 79 where one or more elements further comprise one or more elements of value.

88. (new) The method of claim 79 where one or more outputs further comprise one or more components of value.

89. (new) The method of claim 79 where a series of time periods contains time periods selected from the group consisting of historical time periods, future time periods and combinations thereof.

90. (new) The method of claim 79 where the one or more pre programmed functions are selected from the group consisting of average, rolling average, time delay, trend, average time delay, rolling average time delay, ratio, average ratio, rolling average ratio, slope, average slope, rolling average slope and combinations thereof.

91. (new) The method of claim 79 that further comprises: normalizing one or more sets of raw and transformed transaction data by element, refining the sets of raw and transformed transaction data by element, creating a summary of the refined transaction data set for each element, and using the element summaries as inputs to a predictive model.

92. (new) A computer readable medium of building predictive models from transaction data, comprising:

aggregating data from a plurality of transaction systems covering a series of time periods for one or more elements and one or more outputs;

transforming said element data in accordance with one or more pre-programmed functions;

establishing a plurality of input nodes, a plurality of hidden nodes and an output node for a neural network model for each output;

inputting the raw and transformed transaction data into each neural network model using a separate input node for untransformed transaction data and each preprogrammed transformation function by element for all time periods in the series;

training each neural network model using said inputs until an error function associated with an output value is minimized; and

using one or more weights from the trained neural network models to identify a set of raw and transformed transaction data by element and output that will be used as an input to one or more predictive models.

93. (new) The computer readable medium of claim 92 where a plurality of input nodes is set equal to one plus the number of elements times one plus the number of preprogrammed functions used to transform transaction data.

94. (new) The computer readable medium of claim 92 where a plurality of hidden nodes is set equal to one plus the number of input nodes.

95. (new) The computer readable medium of claim 92, where an error function further comprises ERR  $(W)_k = 1/2 (R_k - Y(W))^2$ .

96. (new) The computer readable medium of claim 92 where a set of raw and transformed transaction data that will be used as an input to a predictive model further comprises a set of numbers.

97. (new) The computer readable medium of claim 92 where one or more predictive models further comprises one or more neural network models.

98. (new) The computer readable medium of claim 92 where training a neural network model further comprises using a genetic algorithm to complete the training.

99. (new) The computer readable medium of claim 92 where training a neural network model further comprises using a back propagation algorithm to complete the training.

To: Frantzy Poinvil Page 5 of 8

100. (new) The computer readable medium of claim 92 where one or more elements further comprise one or more elements of value.

101. (new) The computer readable medium of claim 92 where one or more outputs further comprise one or more components of value.

102. (new) The computer readable medium of claim 92 where a series of time periods contains time periods selected from the group consisting of historical time periods, future time periods and combinations thereof.

103. (new) The computer readable medium of claim 92 where the one or more pre programmed functions are selected from the group consisting of average, rolling average, time delay, trend, average time delay, rolling average time delay, ratio, average ratio, rolling average ratio, slope, average slope, rolling average slope and combinations thereof.

104. (new) The computer readable medium of claim 92 where the method further comprises:

normalizing one or more sets of raw and transformed transaction data by element, refining the sets of raw and transformed transaction data by element, creating a summary of the refined transaction data set for each element, and using the element summaries as inputs to a predictive model.

105. (new) An apparatus for building predictive models from transaction data, comprising:

a plurality of transaction systems,

means for preparing data from said systems for use in processing for a series of time periods for one or more elements and one or more outputs;

means for transforming said element data in accordance with one or more preprogrammed functions;

means for establishing a plurality of input nodes, a plurality of hidden nodes and an output node for a neural network model for each output;

means for inputting the raw and transformed transaction data into each neural network model using a separate input node for untransformed transaction data and

each pre-programmed transformation function by element for all time periods in the

means for training each neural network model using said inputs until an error function associated with an output value is minimized; and

means for using one or more weights from the trained neural network models to identify a set of raw and transformed transaction data by element and output that will be used as an input to one or more predictive models.

106. (new) The apparatus of claim 105 where a plurality of input nodes is set equal to one plus the number of elements times one plus the number of pre-programmed functions used to transform transaction data.

107. (new) The apparatus of claim 105 where a plurality of hidden nodes is set equal to one plus the number of input nodes.

108. (new) The apparatus of claim 105, where an error function further comprises ERR  $(W)_k = 1/2 (R_k - Y(W))^2$ .

109. (new) The apparatus of claim 105 where a set of raw and transformed transaction data that will be used as an input to a predictive model further comprises a set of numbers.

110. (new) The apparatus of claim 105 where one or more predictive models further comprises one or more neural network models.

111. (new) The apparatus of claim 105 where training a neural network model further comprises using a genetic algorithm to complete the training.

112. (new) The apparatus of claim 105 where training a neural network model further comprises using a back propagation algorithm to complete the training.

113. (new) The apparatus of claim 105 where one or more elements further comprise one or more elements of value.

114. (new) The apparatus of claim 105 where one or more outputs further comprise one or more components of value.

115. (new) The apparatus of claim 105 where a series of time periods contains time periods selected from the group consisting of historical time periods, future time periods and combinations thereof.

116. (new) The apparatus of claim 105 where the one or more pre programmed functions are selected from the group consisting of average, rolling average, time delay, trend, average time delay, rolling average time delay, ratio, average ratio, rolling average ratio, slope, average slope, rolling average slope and combinations thereof.

117. (new) The apparatus of claim 105 where preparing data for use in processing further comprises integrating, converting and storing data from a plurality of systems in accordance with a common data dictionary.

118. (new) The apparatus of claim 105 that further comprises:

means for normalizing one or more sets of raw and transformed transaction data by element.

means for refining the sets of raw and transformed transaction data by element, means for creating a summary of the refined transaction data set for each element, and

means for using the element summaries as inputs to a predictive model.

To: Frantzy Poinvil Page 7 of 8